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INDUSTRY MOMENTUM CRASHES

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Abstract

Industry momentum strategies produce strong returns, but these strategies also experience infrequent periods of negative returns similar to stock momentum strategies. Momentum crashes are most likely to occur in bear markets when the contemporaneous market return is positive as a result of high loser portfolio returns. Industry momentum strategies have had similar behaviour to written call options during bear markets, but in more recent data the option-like behaviour has disappeared. This bear market optionality is not as strong as it has been documented to be in stock momentum strategies.

Keywords Market anomalies, Market efficiency, Momentum

1 INTRODUCTION

The momentum anomaly, introduced by Jegadeesh and Titman (1993), has been one of the most debated topics in the literature. Price momentum can be described as the subsequent outperformance of the securities with relatively high past returns and subsequent underperformance for the securities with low past returns. It has been detected across multiple asset classes and regions (Asness, Moskowitz and Pedersen (2008) for summary).

Although momentum has been profitable strategy, there has been infrequent periods with poor returns, i.e. momentum crashes. Daniel and Moskowitz (2016) find that momentum crashes occur in panic states after market declines during market rebounds. During the market rebound the losers, which the winner-minus-loser (WML) portfolio is short, experience strong gains, resulting in negative returns for the WML portfolio. In effect, the WML behaves like written call option on the market during bear markets. When the market is falling the WML portfolio will gain little but when the market rebounds it will lose much. This is based on time-varying beta. Daniel and Moskowitz (2016) document momentum crashes across multiple markets and asset classes.

Another interesting finding is that momentum works also in industry level. Moskowitz and Grinblatt (1999) claim that industry momentum strategies explain the risk adjusted outperformance of momentum. But according to Grundy and Martin (2001) industry momentum does not alone explain the profitability of momentum. Nonetheless industry momentum strategies have produced high risk-adjusted returns in US.

So far there has been no evidence of the optionality effect in industry momentum. Grobys, Ruotsalainen and Äijö (2018) find that certain industry momentum strategies do not exhibit same optionality effects as Daniel and Moskowitz (2016) observed in stock momentum strategies. My goal is to do further research into momentum crashes in the industry setting. I ask the question does the industry momentum have time-varying betas, and therefore written call option like behaviour in bear markets, and does it result to momentum crashes as Daniel and Moskowitz observed in individual stock momentum. I use three different industry universes with 17, 30 and 49 industries to analyse the difference in results of broader versus narrower industry classifications.

First, I study the characteristic of industry momentum using the three different industry universes and strategy with 12-month formation period and one-month holding period. Comparing the returns of the winner-minus-loser portfolios, the 49-industry momentum has higher returns than the 17 and 30-industry momentum WML portfolios. But when using 49 industries to construct the momentum portfolios the negative skewness is very high (-6.47), whereas with 17 and 30 industries the negative skewness is not as high (-1.97 and -1.87) but still higher than the markets' skewness (-0.55). This is in line with Barrosa and Santa-Clara (2015) who find that momentum strategies have large excess kurtosis and negative skewness.

The worst return months for the industry momentum WML portfolios are in bear markets when the contemporaneous market returns are positive. This is consistent with Daniel and Moskowitz's (2016) findings. The time-varying beta of the loser and winner momentum portfolios is one of the possible causes of momentum crashes. Grundy and Martin (2001) find that when the market has fallen during the formation period the zero-cost momentum strategy buys stocks with low market betas and sell stocks with high market betas. In effect the strategy has negative beta bet on the market. I find that this is the case also in industry momentum strategies. My results document that during the worst performing momentum months cyclical, high beta, industries are more likely to be in the loser portfolio and defensive, low beta, industries in the winner portfolio. As a result of the negative beta bet in bear markets, when the market starts rebounding the WML portfolio will have negative returns.

The bear market optionality of industry momentum strategies is not as strong as in individual stock momentum. Overall the 49-industry momentum has more significant optionality than 17- and 30-industry momentum portfolios.

To test the robustness of the bear market optionality I try different strategies and divide the sample to two subsamples. All the strategies I test have significant bear market optionality for the 49-industry WML portfolio when regressing over the whole sample, whereas not all 17- and 30-industry WML portfolios have significant optionality. My results also suggest that the behaviour of momentum strategies during bear markets has changed. In the first subsample from July 1927 to March 1973 momentum has negative down-betas in bear markets but in more recent subsample from April 1973 to December of 2018 the WML portfolios have positive down-betas in bear markets. This suggest that the return streams are not anymore similar to written call options during the second subsample, because the industry momentum portfolios have negative returns when the market is going down in bear market and have near zero returns when the market is going up in bear market.

There have been two ways to try to explain the abnormal momentum returns, behavioural and risk-based explanations. Behavioural explanations can be divided to underreaction and delayed overreaction.[1] My paper is related to the risk-based explanations. Most closely my paper is related to Daniel and Moskowitz's (2016), Grundy and Martin's (2001) and Daniel, Jagannathan and Kim's (2019, working paper) empirical work on momentum crashes and time varying systematic risk.

Daniel, Jagannathan and Kim (2019) document how the loser stocks in turbulent times have higher effective leverage and because of it they start to behave as out-of-the money call options and this creates convex payoff structure for these stocks. In effect, when the market starts going up during bear markets, the convexity is realized, and the price of these levered stocks starts increasing rapidly resulting in momentum crash for the WML portfolio. I find that the loser portfolio is the main driver of the optionality effect as Daniel and Moskowitz (2016) observed also in stock momentum.

There are markets where researchers have not found evidence of momentum crashes. For example, in recent paper Goetzmann and Huang (2018) don't find similar momentum crashes in imperial Russia from 1865 to 1914, but they still find abnormal returns for momentum strategies. Imperial Russian stock market is not similar to today's stock market in US, but it does raise the question are these crashes the result of modern institutional features. For example, Goetzmann and Huang (2018) note that delegated management, e.g. mutual funds, are absent in 19th century Russian stock market. Vayanos and Woolley (2011) propose a theory of momentum based on delegated portfolio management. On the other hand, Chabot et al. (2014) report abnormal returns and momentum crashes using data from London stock exchange during period from 1866 to 1907 where the role of delegated management was limited.

This paper is structured as follows: Section 2 describes the data and the industry momentum portfolio construction. It also shows the industry momentum return characteristics during the sample period. Section 3 shows industry momentum drawdowns and the worst return months. Section 4 examines the time varying beta and option like payoffs of industry momentum. In section 5, I test different momentum strategies and divide sample to two subsamples to assess the robustness of my results. Section 6 concludes this paper.

[1] For overreaction explanation see e.g. De Long's et al. (1990) model and for overreaction see e.g. Barberis, Shleifer, and Vishny (1998). For risk-based explanation see e.g. Griffin, Ji, and Martin (2003). For overview of momentum premium explanations you can see Moskowitz's (2010) AQR white paper, Explanations for the momentum premium.

2 INDUSTRY MOMENTUM

In this section I present my analysis of industry momentum using three different US industry universes over the 1927/7-2018/12 time period.

2.1 Industry momentum portfolio construction

My data source is Kenneth French's data library. I use monthly returns to create momentum portfolios for three different industry universes. Namely 17, 30 and 49 value weighted industry returns provided by Kenneth French's data library. In each of these industry portfolios the NYSE, AMEX and NASDAQ stocks are assigned to an industry portfolio based on its four-digit SIC code. For example, in the 30 industry portfolios the monthly stock returns are assigned to 30 industries and then the value weighted industry return is calculated. More information in Kenneth French's website.

To form the industry momentum portfolios for these three industry universes, I first rank the industries based on their 12-month cumulative returns before the formation date, t-12 to t-1 returns. I don't use the one-month gap between the formation period and holding period. Moskowitz and Grinblatt's (1999) results found that large part of the industry profitability comes from the first month after the formation period. This is the exact opposite what have been observed in in individual stock momentum strategies, i.e. there has been one-month reversal effect (Jegadeesh (1990)). These industries are then placed into one of six portfolios based on their ranking. After assigning the industries to portfolios I calculate the one-month equal-weighted holding period returns for each momentum portfolio. After one month I rank the industries again based on the 12-month formation period and assign them to the six momentum portfolios.

The 30-industry portfolios are divided to six portfolios so that every momentum portfolio has five industries. 17 and 49 industries cannot be divided equally between the six momentum portfolios, so I made sure that the winner and loser portfolios have the same number of industries, because my focus is on those portfolios. This means that the winner and loser portfolio each have three industries when using 17 industries to create the momentum portfolios. For 49-industry momentum the number of industries in portfolio changes because at the beginning of the sample some industries do not have returns available. At the start there are 40 industries with returns. The number of industries with returns grows gradually until July of 1970 when all 49 industries have returns available. The winner and loser portfolios first have seven industries, but it changes to eight when 47 industry returns become available in July of 1964 and the number of industries in each winner and loser portfolio will stay at eight for the rest of the sample.[2]

As excess market return I use the value-weighted returns of listed firms in CRSP, and the risk-free rate is the one-month Treasury bill rate. Both obtained from Kenneth French's website.

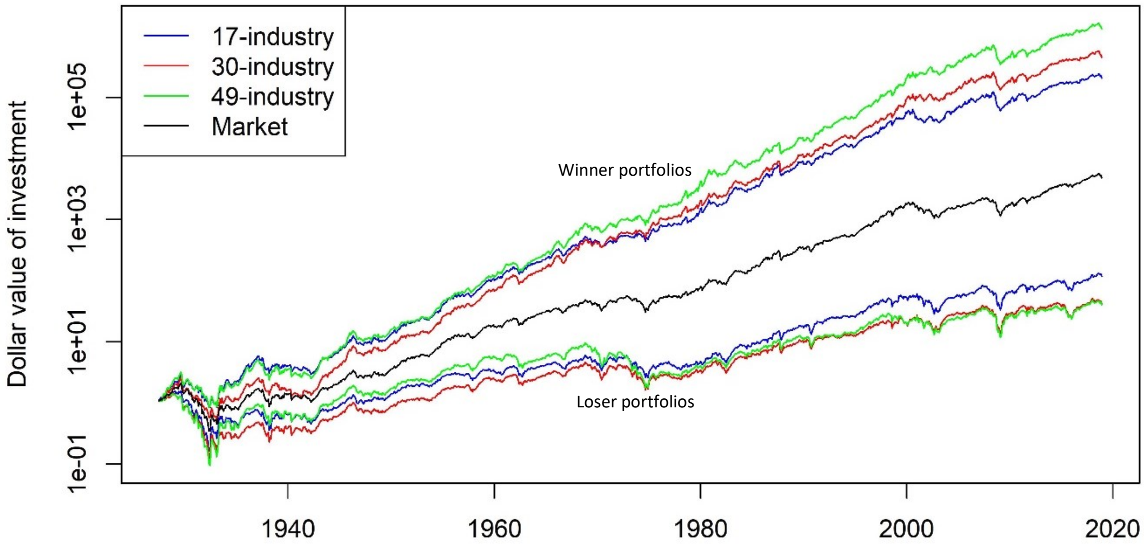


Fig 1. Winner and loser portfolios' cumulative returns of the three different industry universes, 1927/7:2018/12. Plotted are the 17-industry momentum winner and loser portfolios (blue), 30-industry momentum winner and loser portfolios (red), 49-industry momentum winners and loser portfolios (green) and the market return (CRSP value-weighted index), (black) cumulative returns. The loser and winner portfolios, for each industry universe, are plotted with same colour and the winner portfolio's cumulative returns are above the market return and loser portfolio's below the market return.

2.2 Industry momentum performance

Figure 1 presents the cumulative returns for the three winner and loser portfolios of the 17-, 30- and 49-industry momentum strategies and the cumulative market return. All three winner portfolios

[2] I calculated how many firms each momentum portfolio has on average. The 49-industry loser portfolio has on average 403 firms and the winner portfolio has 409 firms on average. The 30-industry momentum loser portfolio has 441 firms and winner portfolio 443 firms on average. The 17-industry losers and winners have 450 and 449 firms on average. Interestingly, in all three cases the winner and loser portfolios have the least firms on average in the portfolios compared to the other four portfolios. This could simply mean that industries with less firms have more volatile average returns, since each stock's return has larger effects on the average industry return, and therefore they are more likely to appear in the winner and loser portfolios.

outperform the market and the loser portfolios underperform the market. Table 1 presents the return characteristics for winner-minus-loser (WML) portfolios from 1927:07 to 2018:12 calculated for the three different industry universes. WML returns have been highest for the 49-industry momentum and lowest for the 17-industry momentum. For all three strategies the winner portfolio seems to produce most of the profits for the WML portfolio. Moskowitz and Grinblatt (1999) also find that bulk of the zero-cost industry momentum portfolio's profits are produced by the buy side rather than the sell side. In individual stock momentum large part of the profits are produced by the sell side (e.g. Hong, Lim, and Stein, 2000).

All three strategies produce alpha and have slightly negative betas. 49-industry momentum has also the highest volatility and 17-industry momentum has the lowest volatility. The 30-industry momentum has the highest Sharpe since its volatility is lower than the 49-industry momentum's volatility. The 49-industry loser portfolio has large kurtosis (31.30) compared to market and the other momentum portfolios. This also results in as large kurtosis for the 49-industry WML portfolio (31.66).

Table. 1

Industry momentum portfolio characteristics, 1927:07–2018:12.

This table presents characteristics of the monthly momentum excess returns of loser, winner and zero-investment winner-minus-loser portfolio, which is short the loser and long the winner portfolio. Presented for three different industry universes. The sample period is from 1927:07 through 2018:12. The data for the value weighted industry returns are from Kenneth French's website. The loser portfolio contains 1/6 of the industries that have performed the worst during the past 12 months. The winner portfolio contains 1/6 of the industries that have had the best returns during the past 12 months. The portfolios are constructed every month according to the ranked returns during the 12-month formation period. The mean excess return, standard deviation, and alpha are annualized and in percent. SR is the annualized Sharpe Ratio. The α, t(α), and β are from a full-period regression of each portfolio's excess return on the excess return of the market. Kurtosis is measured using monthly returns. For winner and loser portfolios sk(m) (sk(d)) denotes the full-period realized skewness of the monthly (daily) log returns (not excess) to the portfolios. For WML, sk is the realized skewness of $log(1 + r_{WML} + rf)$.

	17 industries			30 industries			49 industries			Market
	Loser	Winner	WML	Loser	Winner	WML	Loser	Winner	WML	
$\overline{r - rf}$	4.53	12.09	7.56	3.52	13.02	9.50	4.30	14.41	10.11	7.72
σ	23.18	19.60	16.41	23.56	19.92	17.19	27.69	20.88	19.81	18.55
α	-4.17	4.85	9.02	-5.21	5.83	11.04	-5.59	6.79	12.37	0.00
t(α)	(-3.94)	(5.09)	(5.34)	(-4.59)	(5.56)	(6.24)	(-3.72)	(6.40)	(6.16)	(0.00)
β	1.13	0.94	-0.19	1.13	0.93	-0.20	1.28	0.99	-0.29	1.00
SR	0.20	0.62	0.46	0.15	0.65	0.55	0.16	0.69	0.51	0.42
Kurt	16.85	6.42	10.59	13.09	6.44	10.66	31.30	6.43	31.66	10.79
SK(m)	-0.04	-0.83	-1.97	-0.39	-0.68	-1.87	0.51	-0.78	-6.47	-0.55
SK(d)	0.25	-0.89	-1.08	0.16	-0.58	-0.79	0.35	-0.93	-1.71	-0.43

All the industry momentum winner portfolios have basically same kurtosis (6.4), which is lower than the market's kurtosis whereas loser portfolios' kurtosis is higher than the markets. This entails that most of the tail-events for the WML portfolio are result of the loser portfolio.

Another big difference between the industry momentum strategies is the monthly skewness of the WML returns. The 49-industries strategy has substantially larger negative skewness (-6.47) compared to the two other strategies (-1.97, -1.87). The monthly skewness of the 49-industry loser portfolio is positive (0.51), whereas it is negative for the other two momentum strategies. This positive loser portfolio skewness is the main driver of the large negative skewness for the 49-industry WML portfolio. (The high kurtosis and negative skewness of the 49-industry momentum are result of couple tail observations in the sample.) All WML portfolios have larger monthly and daily skewness than the market. The fact that these momentum strategies have outperformed the market and have larger negative skewness is in line with the findings that risk premium is correlated with the skewness of the returns (see for e.g. Lempérière et al. (2014)).

3 INDUSTRY MOMENTUM DRAWDOWNS AND CRASHES

3.1 Industry momentum drawdowns

To get better sense of industry momentum performance during times of stress I plot drawdowns of the three industry momentum winner-minus-loser (WML) portfolios and the market drawdowns. To measure the drawdowns, I take the cumulative sum of the monthly log returns. Every month I take the maximum cumulative log return that I have observed from the first observed month (1927/7) to the current month (t) and subtract that by the current month's (t) cumulative log return. If this is subtraction is larger than zero, i.e. the maximum cumulative return from month one to month t is larger than the cumulative return in month t, the strategy is in drawdown and I record this subtraction in my drawdown time series which is plotted in figure 2. If the subtraction is negative it is recorded as zero. [3]

$$c = \{c(t) = \sum_{s=1}^{t} \log[1 + R_{WML,s}] \mid t \in 1, \dots, T\}$$

$$d = \{d(t) = max[0, max[c(s) \mid s \in (1, \dots, t)] - c(t)] \mid t \in 1, \dots, T\}$$

where c is the cumulative log return and d is the drawdown state.

[3] I learned about this method of calculating drawdowns from Robert Frey's lecture 180 years of Market Drawdowns. Available here https://www.youtube.com/watch?v=27x632vOjXk.

Figure 2 shows how the 49-industry WML has one drawdown period that is over 33 years long. This means that if you invested in 49-industry momentum in June 1932 you would get back to even in September 1965. For the market portfolio the longest continuous drawdown period is about 15 years. The 49-industry WML portfolio is in drawdown 85% of the time and out of that it is in over 20% drawdown 60% of the time. The market portfolio is in drawdown 79% of the time and of that it is in large, over 20% drawdown, 45% of the time. Even though the 49-industry WML portfolio has the one long continuous period in drawdown state, there is no big difference between market's and the momentum portfolio's time spent in drawdown stage overall. The 17-industry and 30-industry WML portfolios have very similar amounts of time spent in drawdown state (78% and 82%). The three momentum portfolios also seem to have correlated drawdown behaviour with each other after 1965 when the 49-industry WML portfolio recovers from the momentum crash of 1930's.

Figure 2 shows how short period of extremely negative performance can have big impact on long-term returns. There is reason why investors want to avoid negative tail events. For example, Ruenzi and Weigert (2018) find that controlling for crash sensitivity reduces the profitability of momentum strategies meaningfully.

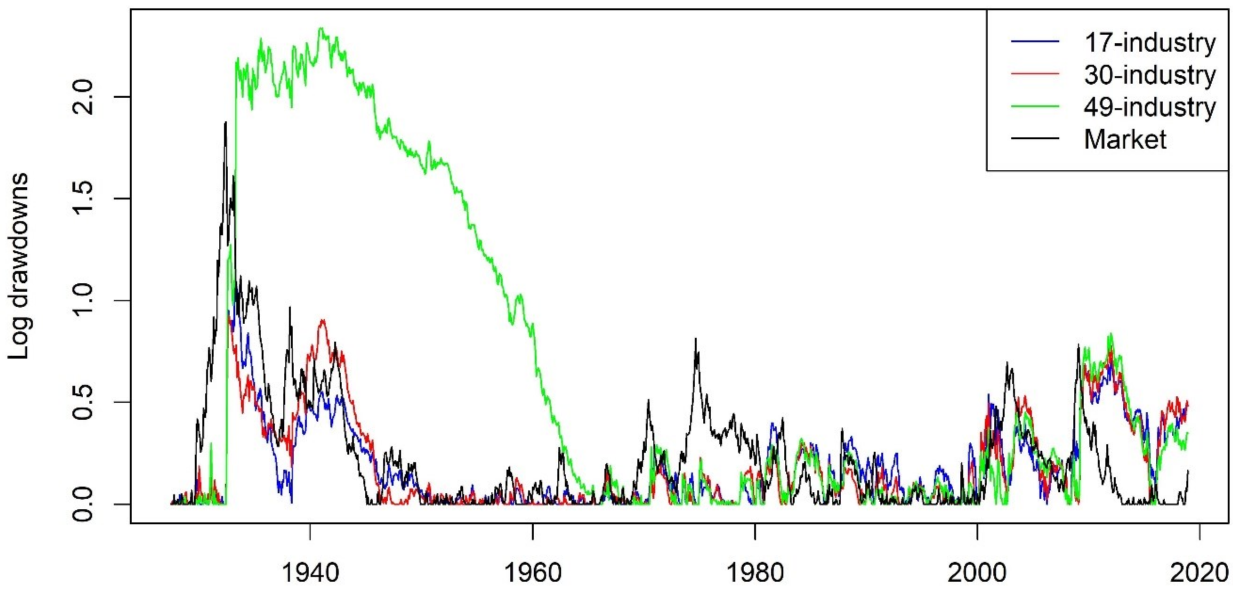


Fig 2. Zero-cost winner-minus-loser (WML) portfolios log drawdowns for three industry universes. Includes also the market portfolios (CRSP value-weighted index) drawdowns.

3.2 Worst monthly returns

Table 2 present the fifteen worst WML return months, and the loser and winner portfolio returns that produced the WML returns, for all the three industry universes. The 49-industrty momentum has two months in the 1930's where the WML returns are extremely bad (-65.21% and -57.91%). In both months the loser portfolio has returns of over 80% and the winner portfolio returns are about 25%. Even though the winner portfolio has good returns during these months, the extremely high returns of the loser portfolio results in the momentum crash. The loser portfolio is the driver of these momentum crashes. In fact, during the 49-industry WML portfolio's 13 (out of the 15) worst performing months the winner portfolio return is positive. For 17-industry and 30-industry WML portfolios' max negative returns are not nearly as high (-38.62 and -36.03%) as the 49-industries worst month. For comparison, market's worst month in the sample is -29.10% in September 1931. This suggest there is larger risk of more negative left tail events for the industry momentum than the market.

Table 2 also presents the prior two-year market returns leading up to worst momentum returns (Mkt-2y). Daniel and Moskowitz (2016) find that 14 out 15 worst months have negative prior two-year market returns for the stock momentum strategy. In industry momentum the results are not as clear. Only 8 out of 15 of prior 2-year market returns leading up to the worst months are negative for the 49-industry momentum. But seven worst return months all have negative prior 2-year market returns. This same pattern seems to be the case also for the 17- and 30-industry strategies. The worst of the worst months have negative prior 2-year returns, but the next worst months mostly have positive returns.

Table 2 also presents the contemporaneous market returns (Mkt_t). Daniel and Moskowitz (2016) document that all of the 15 worst months have positive contemporaneous market returns for the stock momentum strategy. In industry momentum the contemporaneous returns are mostly positive for all industry universes. Again, all the worst of the 15 months have positive contemporaneous market returns. It seems that the worst of the worst months have similar behaviour as observed by Daniel and Moskowitz (2016) in stock momentum, but this effect disappears relatively quickly when we look at the months outside of the worst five. This is because the prior 2-year market returns turn from negative to mostly positive after the five worst months for all three strategies. Also, the industry momentum strategy does not have as large worst monthly performances as does the Daniel and

Table 2

Worst monthly industry momentum returns.

This table lists the 15 worst monthly returns to the winner-minus-loser industry momentum portfolios, WML_t, over the 1927:07–2018:12 time period. Winner and loser portfolio returns that produced the WML return are included. Two-year WML returns (WML-2y) and market returns (Mkt-2y) leading up to the portfolio formation date are included. Also, the contemporaneous market return, Mkt_t, and the 126-day prior beta of the loser and the winner portfolios, regressed over the daily market excess returns, are presented. These results are presented for three different industry universes. All numbers, except betas, in the table are in percent. Months between 1930:01-1934:11 are marked with an asterisk (*) and months between 1999:04-2001:11 are marked with †.

17 industries

								126-day prior beta	
Rank	Month	Loser	Winner	WML_t	WML-2y	Mkt-2y	Mkt_t	Loser	Winner
1	1932:08*	59.33	20.72	-38.62	29.44	-67.59	37.09	1.11	0.68
2	1932:07*	48.54	17.37	-31.18	85.34	-74.74	33.87	1.11	0.67
3	1933:04*	56.14	33.70	-22.44	-29.15	-58.91	38.95	1.34	0.85
4	2009:04	24.18	3.52	-20.66	14.61	-40.62	10.20	1.44	0.72
5	1938:06	33.71	13.35	-20.36	43.94	-27.94	23.87	1.21	0.62
6	1999:04†	22.74	2.66	-20.08	55.63	68.60	4.70	0.68	0.90
7	2001:01†	10.45	-8.30	-18.75	-14.32	10.58	3.67	0.63	1.03
8	2008:07	4.44	-11.50	-15.94	40.21	4.79	-0.62	1.33	1.04
9	2008:09	-6.49	-20.52	-14.03	18.63	3.73	-9.09	1.51	0.81
10	1988:01	7.51	-4.68	-12.19	19.61	18.14	4.50	0.84	1.07
11	1986:09	0.69	-11.44	-12.13	34.17	-8.15	64.43	0.67	1.16
12	2016:04	11.54	-0.40	-11.94	20.32	0.93	10.86	1.36	0.88
13	2000:11*	-3.30	-15.01	-11.71	-0.56	-10.21	37.30	0.46	1.30
14	2001:04*	13.38	2.05	-11.33	-19.80	8.33	-7.11	1.00	0.63
15	1986:08	13.01	2.13	-10.87	44.56	6.53	71.50	0.61	1.17
Avg.		19.73	1.58	-18.15	22.84	0.87	9.64	1.02	0.90

30 industries

								126-day prior beta	
Rank	Month	Loser	Winner	WML_t	WML-2y	Mkt-2y	Mkt_t	Loser	Winner
1	1932:08*	55.68	19.65	-36.03	19.98	-67.59	37.09	0.94	0.67
2	2009:04	36.96	3.61	-33.35	45.20	-40.62	10.20	1.36	0.78
3	1932:07*	49.05	16.45	-32.60	73.87	-74.74	33.87	0.87	0.66
4	1938:06	33.43	10.16	-23.27	21.97	-27.94	23.87	1.17	0.48
5	2001:01†	13.78	-5.27	-19.05	37.00	10.58	3.67	0.45	0.80
6	1939:09	21.67	3.88	-17.79	-11.04	-21.59	16.89	1.11	0.93
7	1930:01*	11.11	-5.93	-17.04	91.09	18.34	5.75	0.83	1.09
8	2000:05†	7.14	-6.94	-14.08	81.41	32.54	-3.92	0.41	1.21
9	2000:09†	0.26	-13.10	-13.36	52.26	69.18	-4.94	0.42	1.20
10	2001:11†	12.63	-0.47	-13.10	19.55	-19.90	7.71	1.40	0.61
11	1999:04†	19.30	6.73	-12.57	66.09	68.60	4.70	0.74	1.09
12	2011:10	21.60	9.31	-12.30	2.57	11.48	11.35	1.11	1.15
13	2016:04	10.56	-1.63	-12.19	47.38	10.86	0.93	1.52	0.82
14	1973:07	13.69	1.82	-11.86	62.49	2.52	5.69	1.17	0.82
15	2009:07	16.75	5.23	-11.53	-1.90	-34.80	7.73	1.59	0.61
Avg.		21.57	2.90	-18.67	40.53	-4.20	10.71	1.01	0.86

49-industries

								126-day prior beta	
Rank	Month	Loser	Winner	WML_t	WML-2y	Mkt-2y	Mkt_t	Loser	Winner
1	1933:05*	90.72	25.51	-65.21	-35.49	-36.63	21.47	1.11	0.68
2	1932:08*	83.45	25.54	-57.91	61.01	-67.59	37.09	1.11	0.67
3	2009:04	38.64	0.73	-37.91	45.83	-40.62	10.20	1.34	0.85
4	1932:07*	44.94	16.98	-27.97	112.01	-74.74	33.87	1.44	0.72
5	1938:06	35.38	12.01	-23.37	32.43	-27.94	23.87	1.21	0.62
6	1970:09	23.44	4.08	-19.36	57.45	-16.42	4.72	0.68	0.90
7	1939:09	30.22	11.49	-18.73	6.57	-21.59	16.89	0.63	1.03
8	1934:11*	31.12	12.85	-18.27	-51.69	46.79	8.34	1.33	1.04
9	1931:02*	23.72	5.67	-18.05	56.82	-38.56	10.92	1.51	0.81
10	2001:01†	11.42	-5.93	-17.35	81.65	10.58	3.67	0.84	1.07
11	1935:05	17.13	1.42	-15.72	-61.15	3.48	31.18	0.67	1.16
12	2001:11†	13.38	-0.84	-14.22	45.98	7.71	-19.90	1.36	0.88
13	1975:01	28.05	14.42	-13.63	137.62	14.24	-41.65	0.46	1.30
14	1973:07	16.63	3.03	-13.59	100.77	5.69	2.52	1.00	0.63
15	2002:11†	13.55	0.13	-13.42	58.21	6.08	-36.22	0.61	1.17
Avg.		33.45	8.47	-24.98	43.20	-22.05	13.88	1.13	0.79

Moskowitz's (2016) stock momentum strategy. These results suggest that industry momentum does not have as large tail event risk as the individual stock momentum strategies.

The worst return months are clustered around certain periods, namely during the dot-com crash around 2000 and the great depression in 1930's. During both periods market volatility was high, and investors lost money. During these times investors are especially hurt by negative returns.

The table 2 presents the 126-day betas, prior to the worst return months, of the loser and winner portfolios, regressed over the daily excess market returns. The average 126-day prior beta over the 15 months for the 49-industry loser portfolio is 1.13, whereas for the winner portfolio it is 0.79. This is expected since most of the months have negative 2-year market returns. This means that the loser portfolio has high beta industries since these have the lowest returns during the formation period. The winner portfolio on the other hand has low beta industries because these perform better during bear markets. The large negative returns for the WML portfolio is produced when the market bounces back and the high beta loser portfolio outperforms the low beta winner portfolio. The 17- and 30-industry loser portfolios have also larger 126-day prior betas than the winner portfolios on average. But this is not the case for all worst performing months. Among the worst performing months there are cases where the 2-year market return is negative, but the winner portfolio has larger 126-day prior beta than the loser portfolio.

Chabot et al. (2014) document that momentum crashes are more likely to happen after good returns for the momentum strategy. Table 2 presents the 2-year prior returns for the WML portfolios (WML-2y). These WML returns leading up to the to the worst return months have been positive most of the time. On average the 49-industry momentum have 2-year return of 43.20% leading up to the crash. There are three months where the 2-year return is over 100%, but the three 2-year returns that are negative are all bad 2-year periods with cumulative returns of -35.49%, -51.69% and -61.15%. Only one 2-year absolute return is under 20% for the 49-industry momentum. Similarly, 17- and 30-industry have mostly positive two-year WML returns, but there is not as large variation.

For comparison, the best performing months for the three strategies are: 21.67% (49-industry), 19.25% (30-ind), and 15.86% (17-ind). These are meaningfully lower than the negative returns of the worst months. This is expected because of the negative skewness of these momentum strategies. For comparison, the markets best monthly return is 38.95%. This gives some idea of momentum's return stream being similar to shorting volatility. Making frequent small gains with infrequent periods of large losses.

3.3 Portfolios during the worst months

To get better sense of industry momentum during the worst monthly performances I look at the industries in the winner and loser portfolios during these worst months. Out of the 15 worst return months for the 49-industry momentum, the highest number of appearances in the winner portfolio are tobacco with ten, communications with six, and five appearances for both the agriculture and pharmaceutical industries. The highest number of appearances in the loser portfolio during these months are real estate with 11, recreation and paper both with seven, and computer software and electronic equipment both with six appearances. Three of the four industries with highest number appearances in the winner portfolio, tobacco, agriculture and pharmaceutical, are not once in the loser portfolio during these 15 months. Real estate is once, recreational and electronic equipment twice and paper and computer software zero times in the winner portfolio during these 15 worst performing months. Similar industries are in 30-industry momentum winner and loser portfolios during its worst return months. Tobacco (9), services (7) and healthcare (6) with highest number of appearances in the winner portfolio and coal (7), steel (7) and textiles (6) with most appearances in the loser portfolio. Comparing the three industry universes, the maximum number of appearances by one industry either in the loser or winner portfolio is highest for the 49-industry momentum. This all suggest that there might be some industry characteristics that makes certain industries more likely to be in winner or loser portfolio during momentum crashes. Looking at the appearances it seems that cyclical industries are more likely to be in the loser portfolio whereas defensive industries are more likely to appear in the winner portfolio during the momentum crashes. Tables of the number of appearances in these portfolios for the 49-industy and 30-industry momentum is presented in the appendix A.

To dig deeper I present the 17-industry momentum winner and loser portfolios in more detail. Table 3 documents that the 17-industry momentum have cyclical industries, consumer durables nine times, steel seven times and cars five times, in the loser portfolio during the worst performing months. Defensive industries consumer (includes drugs, soap, perfumes and tobacco) with eight and food with seven appearances in the winner portfolio during these worst performing months. Table 3 presents the market beta, measured regressing the industry return on the market excess returns over the whole sample. The industries that appear in the winner portfolio during these months seem also to be the industries with low betas and the industries in the loser portfolio have industries with higher betas on average. For example, durables, which appears most in the loser portfolio during the

15 worst months has beta of 1.25 during the whole sample. On the other hand, the consumer industry which appeared most in the winner industry, has beta of 0.72.

The table 3 also shows that none of the industries control the winner and loser portfolios when we look at the whole sample period. This is also observed by Moskowitz and Grinblatt (1999) with their 20 industries. In my momentum portfolios steel appeared most in the loser portfolio with 320 monthly (27%) appearances in the loser portfolio and consumer in the winner portfolio with 279 months (24%) in the winner portfolio. These appearances in the winner and loser portfolios over the whole sample does not seem to explain why there is clearly differences when we compare only the appearances in the 15 worst return months. For example, the car industry appears 23% of the time in the winner portfolio but have zero appearances in the winner portfolio during the 15 worst return months. On the other hand, car industry appears 20% of the time in the loser portfolio and have five appearances during the worst performing months.

Table 3
Summary statistics of the 17-industry momentum.
This table presents the percentage of the months that the industry is in the winner and loser portfolios, average rank where each month the 17th ranked industry has the highest returns and first ranked the worst returns during the formation period. The market beta is measured regressing the industry returns on the market excess returns over the whole period. The last two columns show the times the industry has been in the winner or loser portfolio during the worst 15 return months for the 17-industry WML portfolio. The statistics are measured using time period from 1927:07 to 2018:12. The industries are sorted by the number of times the industry appeared in the loser portfolio during the worst WML return months.

	% of months in				No. of Apps during worst 15 months	
Industry	Loser	Winner	Avg. Rank	Market β	Loser	Winner
Consumer Durables	20 %	15 %	8.37	1.25	9	0
Steel Works	27 %	19 %	8.20	1.35	7	2
Cars	20 %	23 %	9.13	1.20	5	0
Transportation	14 %	16 %	9.18	1.14	4	1
Financials	13 %	17 %	9.30	1.16	4	0
Mining and minerals	26 %	20 %	8.58	0.97	3	4
Oil and Petroleum Products	20 %	23 %	9.23	0.87	3	6
Machinery and Business	13 %	17 %	9.22	1.21	2	2
Other	7 %	4 %	8.92	0.88	2	2
Textile, Apparel and Footwear	21 %	21 %	9.11	0.91	1	4
Chemcals	12 %	15 %	9.21	1.04	1	3
Construction	12 %	9 %	9.06	1.16	1	1
Fabricated Products	15 %	11 %	8.91	0.97	1	1
Utilities	20 %	16 %	8.85	0.77	1	2
Retail stores	13 %	18 %	9.29	0.95	1	2
Food	12 %	16 %	9.15	0.75	0	7
Drugs, Soap, Prfums and Tobacco	19 %	24 %	9.29	0.72	0	8

Similar results can be observed with 30- and 49 industry momentums. For example, for the 49-industry momentum real estate (most appearances in the loser portfolio) has beta of 1.29 and the tobacco industry (most appearances in the winner portfolio) has beta of 0.62. Same tables for the 30- and 49-industry momentums are in the appendix A.

Winner portfolios have more defensive industries and loser portfolio more cyclical industries in the portfolio during momentum crashes. This is in line with, Daniel and Markowitz's (2016) observation that the loser portfolio has more cyclical stocks and the winner portfolio has more defensive stocks in the portfolio. This makes sense since in bear markets the worst performers are the cyclical high beta stocks and the winners are the more stable lower beta stocks and when the market starts rising the high cyclical industries, which the WML portfolio is short, will bounce back, but the defensive industries, which the WML portfolio is long, will not have as strong uptick resulting in momentum crash.

4 INDUSTRY MOMENTUM BETAS AND OPTIONALITY-EFFECTS

4.1 Time-varying beta

By construction when market has negative returns during the formation period the loser portfolio has high beta stocks and the winner portfolio has low beta stocks and vice versa when the market performs well. In figure 3 I have plotted the 126-day rolling market betas with ten daily lags for the winner and loser portfolios of the 49-industry momentum using daily returns. Same method is used by Daniel and Moskowitz (2016). The daily regression I use is of the form

$$\tilde{r}_{i,t}^{e} = \beta_0 \tilde{r}_{m,t}^{e} + \beta_1 \tilde{r}_{m,t-1}^{e} + \cdots + \beta_{10} \tilde{r}_{m,t-10}^{e} + \tilde{\epsilon}_{i,t}$$

I report the sum of the coefficients $\beta_0 + \beta_1 + \cdots + \beta_{10}$. I have chosen to show two subsamples from 1928 to 1940 and from 1995 to 2018. Most of the momentum crashes occurred during these two periods. The plot of the subsample between these two periods is in the appendix B with the beta plots of the 17- and 30-industry momentums.

At the start of the 1930's the loser portfolio beta jumps higher and stays high for the first half of the decade. This is time when the market volatility was extremely high. On the other hand, the winner beta stays lower for large part of the decade. In the subsample starting from 1995 both winner and loser portfolios start with betas near one, then the loser portfolio beta drops first under 0.5 growing the difference between the betas but jumps soon to over 1.5. At the same time the winner portfolio rolling beta starts dropping, it drops even under zero momentarily. As consequence the difference between the betas grows significantly. Same negative correlation is observable during the 2008 financial crisis. Loser portfolio beta starts rising during the financial crisis and the winner portfolio beta starts decreasing. The winner portfolio beta rises high momentarily, almost to three, before the crisis, at the end of 2006 and stays there for January of 2007. Same thing happens in the summer of 1928 when the winner portfolio beta rises momentarily to over two. These are the times of the last bull runs before the two respective market crashes.

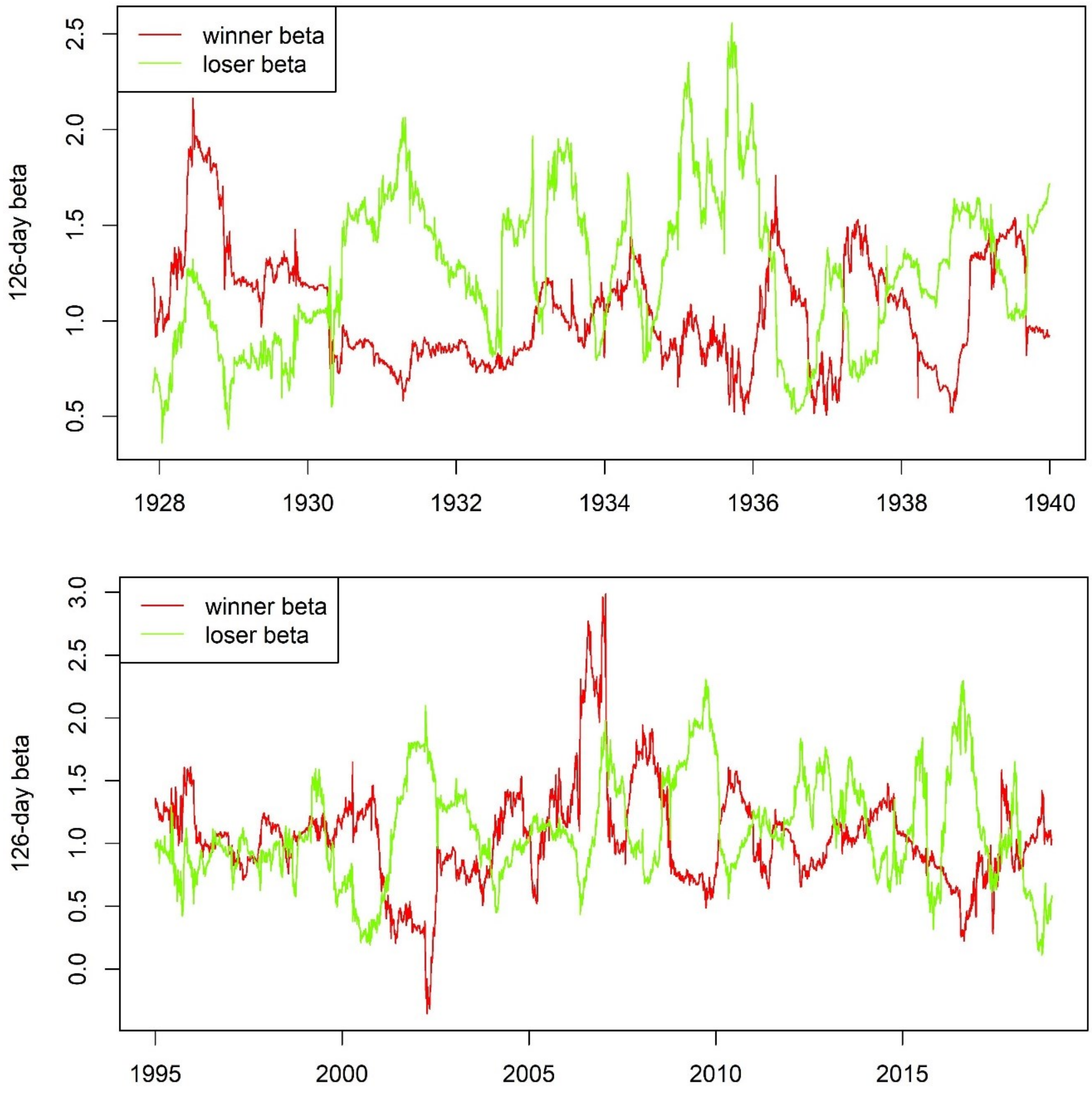


Figure 3 126-day rolling market betas for the 49-industry momentum. Two plots with subsamples from 1928 to 1940 and from 1995 to 2018. Betas are estimated by running 126-day rolling regressions of the daily winner and loser portfolio excess returns over the daily market returns with ten daily lags and summing the betas.

From these figures it seems evident that during volatile periods the loser portfolio beta rises and winner portfolio beta drops causing the WML portfolio to crash when the market starts rising. Before the market crash, during the last bull run the winner portfolio has high betas and loser portfolios low betas. In theory, when the market crashes this should result also to momentum crash, because the high beta winner industries should crash even harder and the low beta loser portfolio will not cushion enough this lose. The data of momentum crashes does not support this, since most of the worst return months are during positive contemporaneous market returns.

4.2 Optionality in industry momentum

In this section I show how optionality is embedded in industry momentum. I do time series regressions using the same three independent variables as Daniel and Moskowitz (2016) used. The dependent variable is $\tilde{R}_{WML,t}$, the WML return in month t. The three independent variables are

1. $\tilde{R}^e_{m,t}$, the market excess return, namely the value-weighted CRSP index excess return.
2. $I_{B,t-1}$, bear market indicator, equals one if the past 24-month (from t-24 to t-1) cumulative market return is negative, zero otherwise.
3. $\tilde{I}_{U,t}$, a contemporaneous up-market indicator equals one if the excess market return is larger than the risk-free rate in month t, zero otherwise.

The regression I use is:

$$\tilde{R}_{WML,t} = \left[\alpha_0 + \alpha_B I_{B,t-1}\right] + \left[\beta_0 + \beta_B I_{B,t-1} + \beta_{B,U} I_{B,t-1}\tilde{I}_{U,t}\right]\tilde{R}^e_{m,t} + \tilde{\varepsilon}_t$$

The goal of $I_{B,t-1}$ is to capture the differences in expected returns and beta during bear markets. $\tilde{I}_{U,t}$ helps capture the differences of the betas during up and down markets in bear markets.

Table 4 presents the regression results of the three industry momentum strategies for the loser, winner and WML portfolios. In bear markets when the contemporaneous market return is negative the beta for the 49-industry WML is -0.3 $\left(= \hat{\beta}_0 + \hat{\beta}_B\right)$, meaning that the WML returns are on average slightly positive. In bear markets when the contemporaneous market return is positive the beta estimate is -0.89 $\left(= \hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U}\right)$, so WML returns are on average highly negative. In effect, the 49-industry momentum is short call option during bear markets. This option-like behaviour is similar

Table 4
Industry momentum portfolio optionality in bear markets.
The table reports results for optionality in bear markets in which, for each of the momentum portfolios, the following regression is estimated:

$$\tilde{R}_{i,t}^{e} = \left[\alpha_0 + \alpha_B I_{B,t-1}\right] + \left[\beta_0 + I_{B,t-1}\left(\beta_B + \tilde{I}_{U,t}\beta_{B,U}\right)\right]\tilde{R}_{m,t}^{e} + \tilde{\varepsilon}_t \ ,$$

where $\tilde{R}_{m}^{e}$ is the value weighted excess market return, $I_{B,t-1}$ is a bear market indicator that equals one if the cumulative market return in the past 24 months is negative and is zero otherwise. $\tilde{I}_{U,t}$ is an indicator that equals one if the contemporaneous excess market return is larger than the risk-free rate in month t and is zero otherwise. The coefficients α_0 and α_B are in percent per month. Results are presented for three industry universes with 17, 30 and 49 industries.

	17 industries			30 industries			49 industries		
	Loser	Winner	WML	Loser	Winner	WML	Loser	Winner	WML
$\hat{\alpha}_0$	-0.41	0.35	0.76	-0.50	0.46	0.96	-0.52	0.54	1.05
	(-4.47)	(4.18)	(5.27)	(-4.95)	(4.94)	(6.19)	(-3.92)	(5.69)	(6.12)
$\hat{\alpha}_B$	0.47	0.39	-0.08	0.76	0.370	-0.40	-0.57	0.39	0.96
	(1.51)	(1.40)	(-0.16)	(2.23)	(1.17)	(-0.76)	(-1.28)	(1.22)	(1.65)
$\hat{\beta}_0$	0.99	1.08	0.10	1.01	1.05	0.04	1.09	1.11	0.02
	(46.03)	(56.56)	(2.91)	(43.30)	(48.80)	(1.00)	(35.97)	(51.12)	(0.47)
$\hat{\beta}_B$	0.25	-0.23	-0.48	0.26	-0.16	-0.42	0.15	-0.17	-0.32
	(4.91)	(-5.21)	(-6.14)	(4.67)	(-3.18)	(-4.96)	(2.13)	(-3.33)	(-3.45)
$\hat{\beta}_{B,U}$	0.09	-0.13	-0.22	-0.02	-0.16	-0.14	0.42	-0.17	-0.59
	(1.33)	(-2.15)	(-2.09)	(-0.27)	(-2.40)	(-1.26)	(4.38)	(-2.41)	(-4.67)

but not as strong as Daniel and Moskowitz observed in stock momentum strategies. This effect is even smaller in 17-industry and 30-industry momentum.

For the 49-industry portfolio most of this optionality effect comes from the loser portfolio. In bear markets during down market the beta estimate is 1.24 (=1.09 + 0.15) for the loser portfolio. In bear market when the market is rising the beta estimate is 1.66 (=1.24 + 0.42) for the losers. For the 49-industry momentum winner portfolio the down-market bear market beta estimate is 0.94 and in up-markets it is 0.77. This means that in bear markets when the market starts going up the loser portfolio's beta rises, and it starts performing better relative to the market whereas the winner portfolio's beta drops in up-market so it cannot match the loser portfolio's performance.

For 17-industry and 30-industry momentum the loser portfolios' $\beta_{B,U}$ is not significant. Because of this there is not similar increase in the loser portfolio returns when the market starts going up in bear market. As a result, the WML portfolios do not have as strong option-like behaviour. The 17-industry WML portfolio still has significant $\beta_{B,U}$, whereas the 30-industry momentum does not.

I also test the regression with bull market indicator instead of bear market indicator to see if there is any asymmetry in the beta during bull markets. None of the three WML portfolios have significant optionality in bull markets.

5 ROBUSTNESS

In this section I’m going to see if different strategies and subsamples produce different results compared to the original strategy I use, namely the strategy with 12-month formation period and one-month holding period with no gap between (12-0-1, formation period - gap -holding period), 1/6 of industries in winner and loser portfolios, industry average returns are value weighted (VW) and momentum portfolios are equal-weighted.

First, I divide the sample to two halves. The two subsamples are from 1927/7 to 1973/3 and from 1973/4 to 2018/12. I calculate the characteristic of these subsamples and repeat the same conditional CAPM regression. The results are summarized in the first two panels of table 5. 49 and 30-industry WML returns do not differ as much between the two subsamples compared to the 17-industry returns. It is meaningfully worse during the more recent subsample (9.38% vs. 5.74%). In the first subsample the WML returns are similar, but in the more recent subsample the narrower industry definition is used the higher the returns. In the winner portfolio both subsamples follow this same pattern, but the loser portfolio returns are reversed, i.e. the 49-industry momentum has the highest loser portfolio returns in first and lowest returns in the second subsample compared to the 17- and 30-industry momentum returns. The skewness is larger in all three industry universes during the first subsample. During the earlier period $\hat{\beta}_B$ is negative in all industry universes, but in the more recent subsample it is positive for all three. This means that during bear markets in the period 1927-1973 the WML portfolio has on average positive returns when the contemporaneous market return is negative. On the other hand, during bear market and negative contemporaneous market returns in period 1973-2018 the WML returns are also negative. $\hat{\beta}_{B,U}$, which captures the optionality in bear markets, is more significant for the first subsample with 17- and 49-industry momentum’s highly significant $\hat{\beta}_{B,U}$ -coefficients. On the other hand, in the second subsample the $\hat{\beta}_{B,U}$ -coefficients are more negative than in the first subsample but they are not as significant.

I also test four different strategies. Summarised results are presented in table 5. In panel C is documented the same strategy as above but with one-month gap. Meaning that the formation period is 11 months and the one month holding period starts one month after the ending of the formation period. The WML returns are smaller than the returns without the gap. This does support Daniel and Moskowitz’s (1999) observation that large part of the returns is produced by the first month after

Table 5

Industry momentum robustness

This table presents the summarized results of six different industry momentum strategies or time periods for three industry universes. First two results are of the strategy 12-0-1 (formation period in months – gap between formation period and holding period in months – holding period in months), 1/6 of industries in winner and loser portfolios, and industry average returns are value weighted (VW) and momentum portfolios are equal-weighted. This is the same strategy I have been focusing on this paper. I have divided this strategy's returns to two subsamples from 1927/7 to 1973/3 and from 1973/4 to 2018/12 and the results are presented in panels A and B. The rest of the strategies show results for the whole sample (1927/7:2018/12) and are variations of the original strategy. Panel C shows results of strategy with one-month gap between the formation period and the holding period (11-1-1) (otherwise same as the original strategy). Panel D has formation period of six months. In panel E the winner and loser portfolio have 1/10 of the total number of industries in their respective portfolios instead of 1/6. In the last panel F, I have used industries' equal-weighted (EW) average returns instead of value-weighted. For all these strategies the table presents the loser, winner and WML portfolios' annual mean return, WML portfolios standard deviation, annualized Sharpe ratio, monthly skewness and the worst monthly return over the whole period. The last two columns present two coefficients of the conditional CAPM regression for the WML portfolios (see table 4) where $\hat{\beta}_B$ shows the difference in the beta during bear market when the contemporaneous market returns are negative and $\hat{\beta}_{B,U}$ shows the difference to $\hat{\beta}_B$ when the contemporaneous market returns are positive in bear market. * = Significant with 5% level, ** = Significant with 1% level, *** = Significant with 0.1% level.

	Loser	Winner	WML	σ	SR	SK(m)	min	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
			A: 12-0-1, 1/6, VW (1927/7:1973/3)						
17	4.60	13.98	9.38	14.81	0.63	-3.87	-38.62	-0.46***	-0.31***
30	3.89	14.36	10.46	15.72	0.67	-3.02	-36.03	-0.38***	-0.24*
49	6.11	15.75	9.64	21.13	0.46	-7.89	-65.21	-0.23*	-0.71***
			B: 12-0-1, 1/6, VW (1973/4:2018/12)						
	Loser	Winner	WML	σ	SR	SK(m)	min	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	4.46	10.20	5.74	17.86	0.32	-0.65	-20.66	0.63***	-0.83*
30	3.14	11.67	8.53	18.54	0.46	-1.06	-33.35	0.50*	-0.61
49	2.48	13.06	10.58	18.39	0.58	-1.44	-37.91	0.58**	-0.73*
			C: 11-1-1, 1/6, VW (1927/7:2018/12)						
	Loser	Winner	WML	σ	SR	SK(m)	min	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	5.25	11.67	6.42	16.39	0.39	-2.05	-36.81	-0.41***	-0.39***
30	5.36	12.64	7.28	17.08	0.43	-2.84	-45.03	-0.32***	-0.46***
49	4.57	14.20	9.62	19.07	0.50	-4.54	-57.28	-0.38***	-0.43***
			D: 6-0-1, 1/6, VW (1927/7:2018/12)						
	Loser	Winner	WML	σ	SR	SK(m)	min	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	5.93	10.77	4.84	15.59	0.31	-1.34	-30.43	-0.25***	-0.39***
30	5.33	11.26	5.93	16.54	0.36	-1.76	-34.95	-0.25***	-0.46***
49	6.35	12.60	6.25	18.09	0.35	-4.02	-49.82	-0.19*	-0.59***
			E: 12-0-1, 1/10, VW (1927/7:2018/12)						
	Loser	Winner	WML	σ	SR	SK(m)	min	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	3.98	12.71	8.73	18.81	0.46	-1.45	-37.66	-0.58***	-0.11
30	2.70	13.21	10.51	21.18	0.50	-1.41	-37.60	-0.35***	-0.27
49	3.97	14.83	10.86	24.62	0.44	-11.08	-83.35	-0.37**	-0.69***
			F: 12-0-1, 1/6, EW (1927/7:2018/12)						
	Loser	Winner	WML	σ	SR	SK(m)	min	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	5.40	16.70	11.30	16.30	0.69	-3.02	-48.94	-0.30***	-0.20
30	4.51	17.36	12.85	16.93	0.76	-1.83	-40.25	-0.44***	0.13
49	6.37	18.09	11.72	18.20	0.64	-2.86	-42.87	-0.31***	-0.32*

the formation period. The coefficient $\hat{\beta}_{B,U}$, which captures the bear market optionality, is highly significant in all three cases, whereas for the strategy without the gap it is highly significant only for the 49-industry and not significant even at 5% level for the 30-industry momentum.

Next, I test strategy that differ from the original strategy in the formation period used, presented in panel D. Instead of using 12-month I use 6-month formation period. The returns are meaningfully lower for this strategy. The 49-indsutry annual mean returns are only 6.25% compared to the returns of the strategy with 12-month formation period, 10.11%. This strategy also has highly significant $\hat{\beta}_{B,U}$ for all three industry universes.

Panel E presents the summarised results for strategy that have 10% of the industries in the winner and loser portfolios, instead of the 1/6 (16.7%) that I have used for the previous strategies. This does improve the mean returns, but the volatility is also higher. For example, the 49-industry WML portfolio, with more extreme winner and loser portfolios, has 0.75% higher annual returns and 4.81 higher standard deviation. The skewness of the 49-industry momentum is -11 whereas it is only about -1.4 for the 17- and 30-industry momentums. The negative skewness increased from -6.5 for 49-industry momentum but it decreased for the other two industry universes compared to the original strategy. The 49-industry WML portfolio's worst month has return of -83.35% which explains much of this extreme negative skewness. Only the 49-industry momentum has highly significant $\hat{\beta}_{B,U}$ and the other two were not significant at 5% level.

The last panel of table 5 summarises the results of the strategy where I used the equal-weighted average returns for the industries instead of value-weighted which I have used before this. Otherwise the strategy is same as the original. These equal-weighted average industry returns are also obtained from Kenneth French's website. (I have used equal-weighting when allocating the industries to the momentum portfolios, but the industry portfolios themselves have been value-weighted until now.) Equal-weighting the industry returns produce higher returns for all the three industry universes compared to the original strategy. Highest increase in the annual mean return is the 3.35% increase for the 30-industry WML portfolio. Sharpe ratios also increased for all. The 30-industry has Sharpe ratio of 0.76 compared to 0.55 in the original strategy. Interestingly the 17-industry momentum's negative skewness increased from -1.97 to -3.02 whereas the 49-industry momentum's negative skewness decreased from -6.47 to -2.86. The bear market optionality coefficient, $\hat{\beta}_{B,U}$, is significant only for the 49-industry momentum.

Testing the robustness using these different strategies document that the Daniel and Moskowitz's (2016) optionality effect is present in industry momentum but it is not as strong as in individual stock momentum. The optionality effect seems to fade away when we use more broad industry definitions. Interestingly this effect is reversed when we look at the subsample from 1973 to 2018. In this subsample the 17-industry has larger $\hat{\beta}_{B,U}$ (-0.83) than the 49-industry (-0.73). This is also true for the other strategies' subsamples presented in table 6. Only the 6-0-1 strategy has equivalent $\hat{\beta}_{B,U}$ for the 17- and 49-industry momentum, for the other three strategies the 17-industry bear market optionality coefficient is larger during the period from 1973 to 2018. In the sample from 1927 to 1973 the 49-indsutry momentum has larger $\hat{\beta}_{B,U}$ than 17-industry momentum for all strategies.

Change in the $\hat{\beta}_B$ is also interesting. This bear market beta is negative for the first subsample for all strategies. In the second subsample it is significantly positive for all tested industry momentum strategies.

I'm going to illustrate how the behaviour of industry momentum strategies in bear markets seems to have changed based on the coefficients (the unconditional beta, β_0, was near zero for all strategies):

Industry momentum behaviour in bear markets in the subsample from 1927 to 1973:

- Negative contemporaneous market returns in bear market $\rightarrow$ Positive momentum returns, because $\beta_B < 0$
- Positive contemporaneous market returns in bear market → High negative momentum returns, because $\beta_{B,U}$ < 0 and $\beta_B + \beta_{B,U} \ll 0$

Industry momentum behaviour in bear markets in the subsample from 1973 to 2018:

- Negative contemporaneous market returns in bear market $\rightarrow$ Negative momentum returns, because $\beta_B > 0$
- Positive contemporaneous market returns in bear market → Returns near zero, because $\beta_{B,U}$ < 0 and $\beta_B + \beta_{B,U} \sim 0$ assuming that $|\beta_B| \sim |\beta_{B,U}|$ (this was the case as we can see from tables 5 and 6)

Even though the $\beta_{B,U}$ -coefficient is larger negative number in the more recent subsample there is no option like payoff patterns because the β_B -coefficient is positive.

Table 6

Industry momentum subsamples

This table presents the summarized results of four different industry momentum strategies' subsamples for three industry universes. I have divided the sample 1927/7:2018/12 to two subsamples 1927/7:1973/3 and 1973/4:2018/12. The results of the strategies presented are variations of the strategy 12-0-1 (formation period in months – gap between formation period and holding period in months – holding period in months), 1/6 of industries in winner and loser portfolios, and industry average returns are value weighted (VW). This is the same strategy I have been focusing on this paper and I refer to it as the "original" strategy. First strategy uses the same strategy but with one-month gap between the formation period and the holding period (11-1-1). Panel B has formation period of six months, otherwise same strategy as the original. In panel C the difference to the original strategy is that the winner and loser portfolio have 1/10 of the total number of industries in their respective portfolios instead of 1/6. In the last panel D I have used industries' equal-weighted (EW) average returns instead of value-weighted. For all these strategies the table presents WML portfolios' annual mean return, annualized Share ratio and monthly skewness of the subsamples. The last two columns present two coefficients of the conditional CAPM regression (see table 4) where $\hat{\beta}_B$ shows the difference in the beta during bear market when the contemporaneous returns are negative and $\hat{\beta}_{B,U}$ shows the difference to $\hat{\beta}_B$ when the contemporaneous market returns are positive in bear market. * = Significant with 5% level, ** = Significant with 1% level, *** = Significant with 0.1% level.

	1927/7:1973/3					1973/4:2018/12				
					A: 11-1-1, 1/6, VW					
	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	7.08	0.46	-3.70	-0.42***	-0.44***	5.76	0.33	-0.69	0.56**	-0.74*
30	7.27	0.46	-4.79	-0.24**	-0.60***	7.29	0.40	-1.17	0.48*	-0.61
49	9.94	0.49	-5.90	-0.31**	-0.52***	9.31	0.52	-1.39	0.52**	-0.64
					B: 6-0-1, 1/6, VW					
	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	6.69	0.49	-2.82	-0.08	-0.52***	2.99	0.17	-0.45	0.62***	-0.72*
30	7.12	0.44	-2.87	-0.09	-0.57***	4.74	0.28	-0.64	0.49**	-0.51
49	6.60	0.35	-5.30	-0.03	-0.68***	5.90	0.34	-1.63	0.56**	-0.75*
					C: 12-0-1, 1/10, VW					
	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	10.01	0.61	-2.79	-0.47***	-0.24*	7.45	0.36	-0.68	0.76***	-0.97*
30	11.29	0.59	-2.42	-0.26*	-0.40**	9.73	0.42	-0.75	0.58*	-0.71
49	10.24	0.38	-11.15	-0.26	-0.82***	11.47	0.52	-1.55	0.69**	-0.88*
					D: 12-0-1, 1/6, EW					
	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$	WML	SR	SK(m)	$\hat{\beta}_B$	$\hat{\beta}_{B,U}$
17	7.66	0.51	-5.81	-0.34***	-0.21*	14.94	0.86	-0.56	0.53**	-0.60
30	9.97	0.64	-3.15	-0.44***	0.08	15.72	0.86	-0.92	0.46*	-0.50
49	8.50	0.44	-3.73	-0.32**	-0.36**	14.94	0.88	-1.07	0.36*	-0.31

Table 6 presents the same four strategies as in table 5, but with the sample divided to two subsamples as in the first two panels for the original strategy in table 5 (1927/7:1973/3 and 1973/4:2018/12). The strategy with the gap month has no big differences in the WML returns between the two subsamples whereas the strategy without the gap does have meaningful differences between the two subsamples. In panel D, with the equal-weighted industry returns, the WML returns are considerably higher during the second period for all industry universes. This is not the case with all the strategies, for example the strategy with six-month formation period (panel B) has lower returns in the second subsample for all industry universes. All the strategies have smaller skewness in second subsample.

The outsized events, especially for the 49-industry momentum, has significant effect on the results. By just taking the two worst 49-industry WML return months out of the sample the negative monthly skewness drops to -1.41 compared to -6.47 in the original sample and kurtosis decreases to 8.69 from 31.66. Also, the $\beta_{B,U}$ -coefficient is not significant for the original 49-industry momentum strategy without the two worst performing months. This suggest that the results are controlled by couple outlier observations, and the applicability of the tools I use to measure the optionality can be questioned since these momentum returns are not normally distributed. On the other hand, these extreme observations are the most important data points since they affect also the long-term performance and therefore they should have large effect in the results.

6 CONCLUSION

The strategy of buying past winners and selling past losers, called price momentum, generates high risk-adjusted returns across variety of asset classes. Momentum strategies experience infrequent periods of meaningful losses referred as momentum crashes. This paper documents that industry momentum does experience worst return months during bear markets when the contemporaneous market return is positive. In bear market the loser industries are cyclical, high beta industries, and the winner industries are more defensive, low beta industries. If the formation period of the zero-cost winner-minus-loser (WML) portfolio is during a bear market the WML portfolio buys the defensive industries and sells the cyclical industries. When the market starts rising the cyclical industries outperform the defensive industries and this results to negative returns for the WML portfolio. Industry momentum with 49 industries has had bigger momentum crashes than strategies with broader industry universes, i.e. less industries, as a consequence of very high loser portfolio returns.

The momentum strategies seem to have similar behaviour to written call options during bear markets (small positive returns when market goes down and large negative returns when market goes up). But it is not as significant as Daniel and Moskowitz observed in stock momentum strategies.

The optionality effect is significant for the 49-industry momentum for most of the strategies I test, whereas in most cases it is not as significant for the 17- and 30-industry momentum strategies. My results also suggest that the optionality effect has disappeared in more recent data. Industry momentum strategies have positive down-market bear market betas and near zero up-market betas in bear market in a subsample from 1973/4 to 2018/12.

One of the suggested reasons for these momentum crashes and the option like behaviour of momentum strategies is Daniel and Markowitz's (2016) idea about option like payoffs of equities based on Merton (1974). This same idea is more developed in Daniel, Jagannathan and Kim's (2019) paper: In bear markets and in volatile market conditions the loser stocks have already dropped in price and are near the value of the underlying assets, the down-market beta is lower, but the up-market beta is higher creating a convex payoff structure for the loser stocks, i.e. the optionality effect. Therefore, when the market starts going up the loser portfolio explodes higher and the WML portfolio crashes.

APPENDIX A

Table A

Summary statistics of the 30-industry momentum.

Tables A and B present the percentage of the months that the industry is in the winner and loser portfolios. Average rank where each month the 30th (49th) ranked industry had the highest returns and first ranked the worst returns during the formation period. The market beta is measured regressing the industry returns on the market excess returns over the whole period. The last two columns show the times the industry has been in the winner and loser portfolio during the worst 15 return months for the 30-industry (49-industry) WML portfolio. All the statistics are measured using time period from 1927:07 to 2018:12. The industries are sorted by the number of times the industry appeared in the winner portfolio during the worst WML return months. Information about the industry definitions can be found in the Kenneth French's website.

	% of months in				No. of Apps during worst 15 months	
Industry	Loser	Winner	Avg. Rank	Loser	Loser	Winner
Smoke	21 %	29 %	16.55	0.62	2	9
Servs	16 %	20 %	16.18	0.81	4	7
Hlth	16 %	21 %	16.17	0.84	0	6
Telcm	20 %	17 %	14.91	0.66	2	5
Food	11 %	12 %	15.67	0.73	1	5
Util	18 %	12 %	15.13	0.77	0	5
Beer	15 %	24 %	16.44	0.93	0	5
Coal	38 %	29 %	14.31	1.29	7	4
Rtail	11 %	13 %	15.90	0.97	2	4
Meals	15 %	18 %	16.10	0.94	3	3
BusEq	15 %	20 %	16.43	1.07	2	3
Oil	18 %	20 %	15.67	0.87	1	3
Steel	25 %	18 %	14.18	1.35	7	2
Games	22 %	26 %	15.95	1.39	5	2
Mines	27 %	18 %	14.37	0.90	3	2
ElcEq	11 %	13 %	16.41	1.28	3	2
Clths	17 %	17 %	15.24	0.81	2	2
Txtls	23 %	20 %	15.26	1.14	6	1
Trans	15 %	12 %	15.14	1.14	4	1
Whlsl	14 %	12 %	14.85	1.09	3	1
Hshld	15 %	10 %	14.93	0.89	2	1
FabPr	10 %	13 %	15.73	1.24	2	1
Paper	9 %	11 %	15.92	0.95	0	1
Books	21 %	17 %	14.66	1.11	5	0
Autos	19 %	22 %	15.55	1.24	5	0
Other	11 %	6 %	14.09	1.06	2	0
Chems	11 %	11 %	15.79	1.04	1	0
Cnstr	8 %	4 %	14.94	1.17	1	0
Carry	14 %	21 %	16.57	1.19	0	0
Fin	10 %	11 %	15.97	1.16	0	0

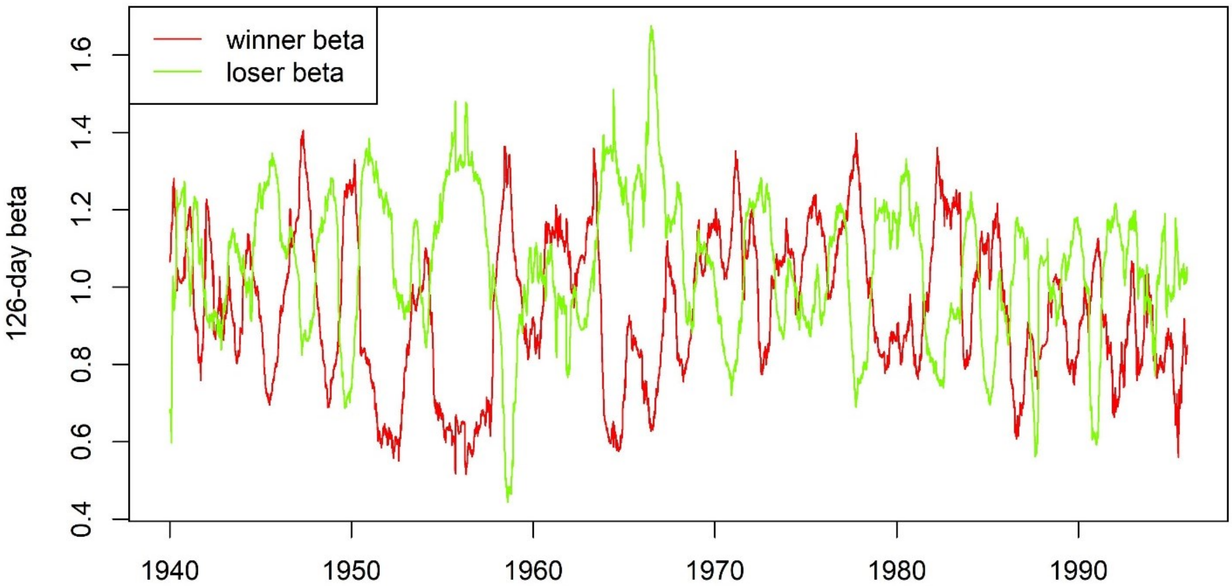
Table B
Summary statistics of the 49-industry momentum.

Industry	% of months in Loser	% of months in Winner	Avg.Rank	Market β	No. of Apps during worst 15 months Loser	No. of Apps during worst 15 months Winner
Smoke	20 %	27 %	25.14	0.62	0	10
Telcm	18 %	17 %	22.59	0.66	3	6
Agric	21 %	15 %	22.27	0.91	0	5
Drugs	15 %	22 %	24.55	0.84	0	5
Coal	35 %	27 %	21.78	1.29	5	4
Beer	13 %	22 %	24.97	0.93	3	4
Aero	15 %	26 %	26.14	1.30	3	4
Gold	39 %	24 %	21.27	-0.04	1	4
Util	16 %	11 %	22.75	0.77	1	4
Food	10 %	12 %	23.79	0.72	0	4
Guns	17 %	25 %	27.62	0.06	0	4
Banks	17 %	20 %	24.55	1.04	0	4
Other	19 %	9 %	20.92	1.06	4	3
Ships	20 %	16 %	22.69	1.17	3	3
LabEq	14 %	18 %	24.64	0.99	2	3
Soda	19 %	26 %	26.20	0.05	1	3
Boxes	12 %	15 %	24.44	0.95	1	3
Hshld	12 %	8 %	22.72	0.89	0	3
MedEq	17 %	21 %	25.05	0.84	0	3
Rubbr	8 %	12 %	24.70	1.11	0	3
Oil	16 %	20 %	23.79	0.87	0	3
Toys	26 %	18 %	21.12	1.21	7	2
Chips	17 %	22 %	24.20	1.34	6	2
PerSv	27 %	17 %	21.81	1.08	5	2
Autos	17 %	20 %	23.11	1.24	2	2
BusSv	8 %	7 %	23.46	0.89	2	2
Clths	14 %	13 %	23.17	0.81	1	2
Rtail	9 %	11 %	23.94	0.97	1	2
Chems	10 %	10 %	23.70	1.04	0	2
Insur	12 %	14 %	23.64	1.12	0	2
RlEst	30 %	20 %	20.71	1.29	11	1
Books	21 %	17 %	22.27	1.11	5	1
Fun	20 %	26 %	25.20	1.42	4	1
Steel	21 %	16 %	21.50	1.35	4	1
Meals	11 %	16 %	24.60	0.94	4	1
Hlth	29 %	26 %	23.61	0.18	3	1
Whlsl	10 %	7 %	22.65	1.09	3	1
ElcEq	8 %	11 %	24.68	1.28	1	1
Mines	21 %	18 %	22.76	0.97	0	1
Paper	17 %	14 %	22.73	1.42	7	0
Softw	26 %	25 %	24.63	0.37	6	0
Cnstr	23 %	19 %	21.72	1.35	4	0
Trans	11 %	10 %	22.89	1.14	3	0
Hardw	14 %	22 %	25.25	1.11	2	0
Txtls	19 %	19 %	23.14	1.14	1	0
BldMt	3 %	3 %	23.35	1.16	1	0
FabPr	23 %	18 %	22.77	0.17	1	0
Fin	11 %	14 %	24.53	1.30	1	0
Mach	8 %	11 %	23.79	1.24	0	0

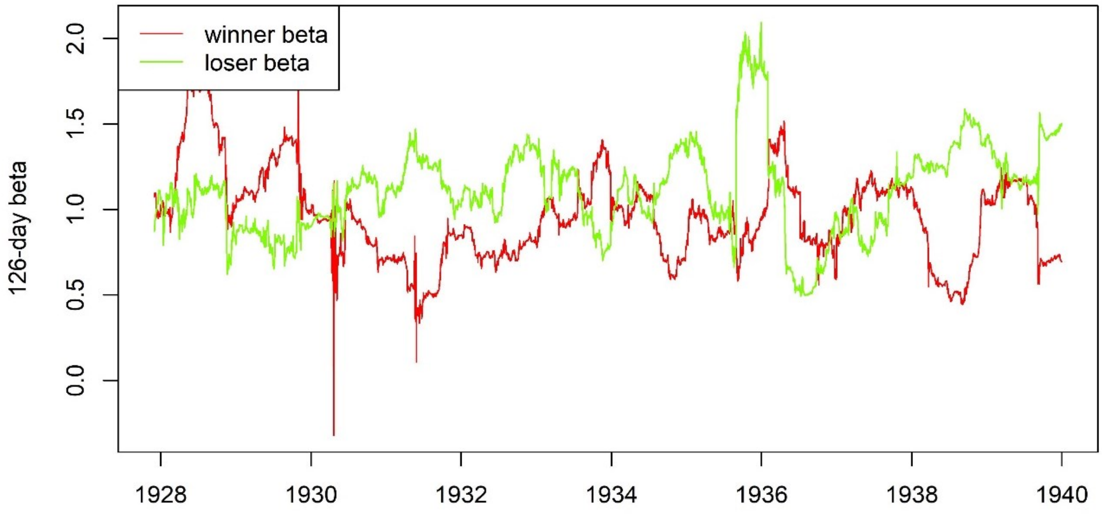
APPENDIX B

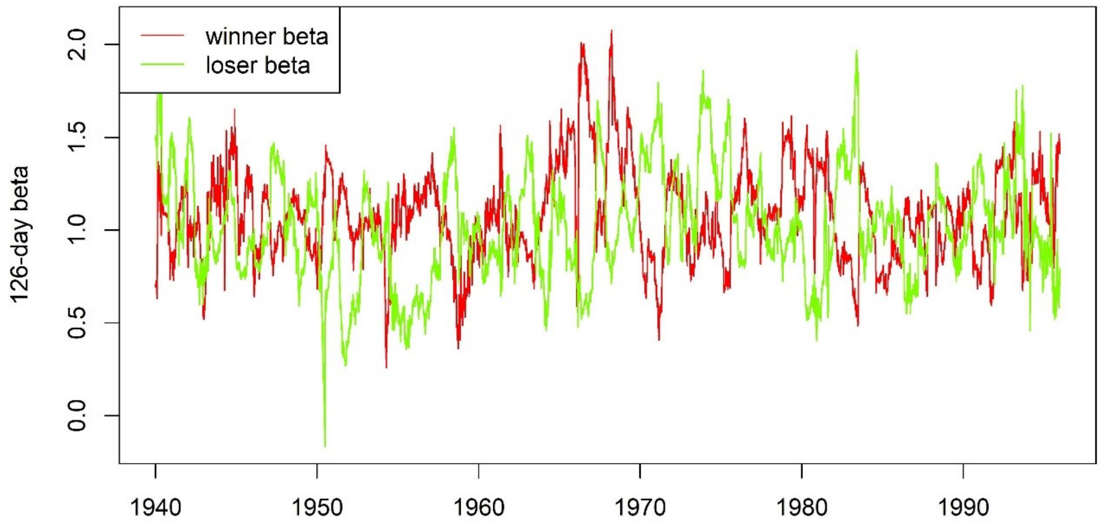
Appendix B presents figures of 126-day rolling market betas for the 49-industry momentum subsample from 1940 to 1995, and of three subsamples for the 30- and 17-industry momentum strategies (1927-1940, 1940-1995 and 1995-2018). Betas are estimated by running 126-day rolling regressions of the daily winner and loser portfolio excess returns over the daily market returns with ten daily lags and summing the betas.

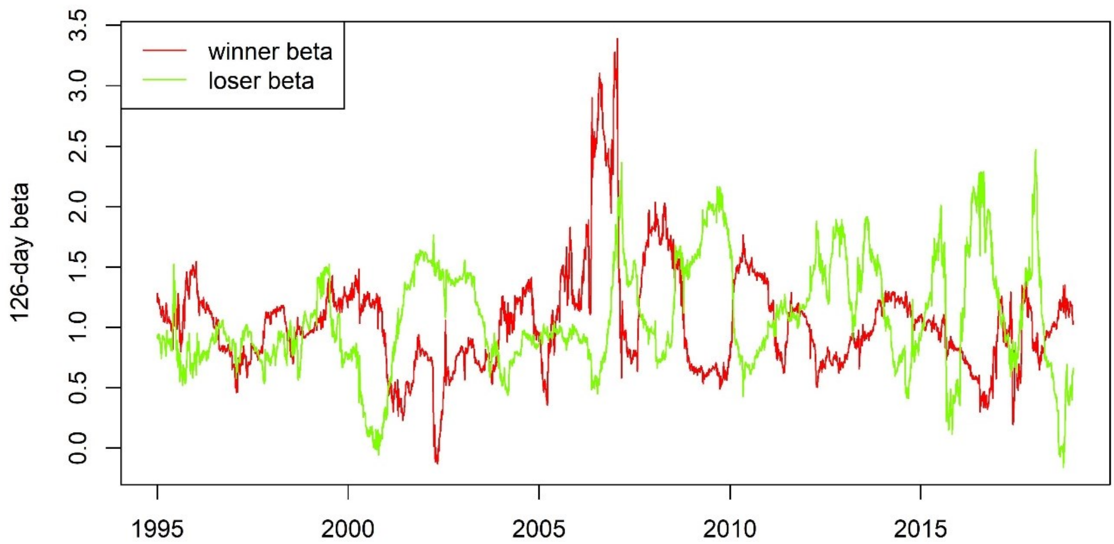
49-industry rolling betas (1940-1995):



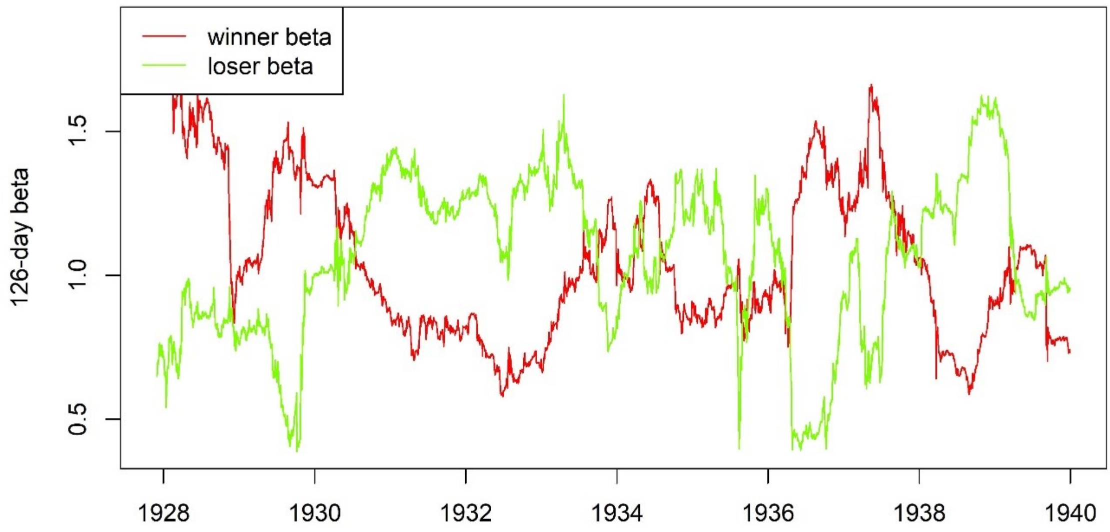
30-industry rolling betas:

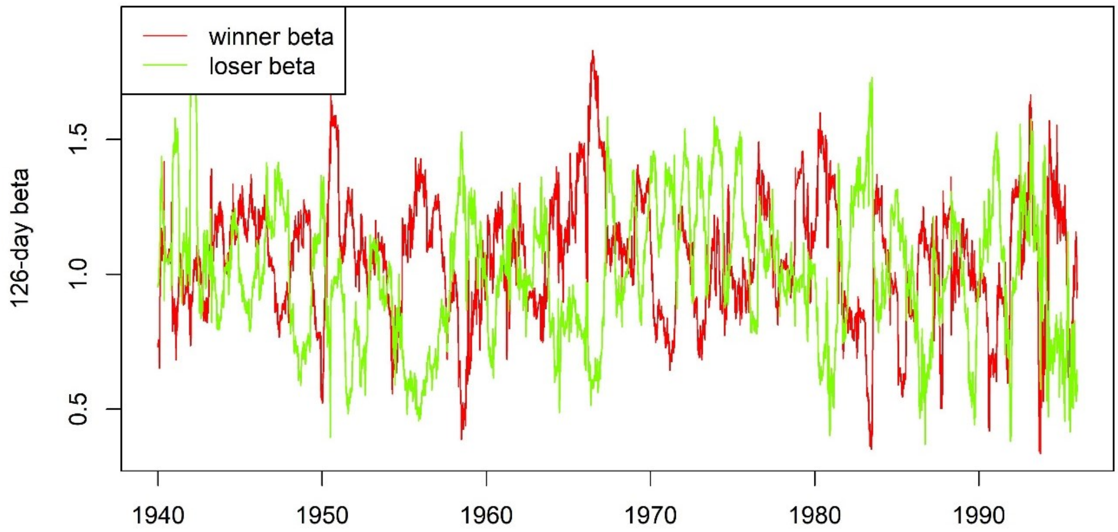


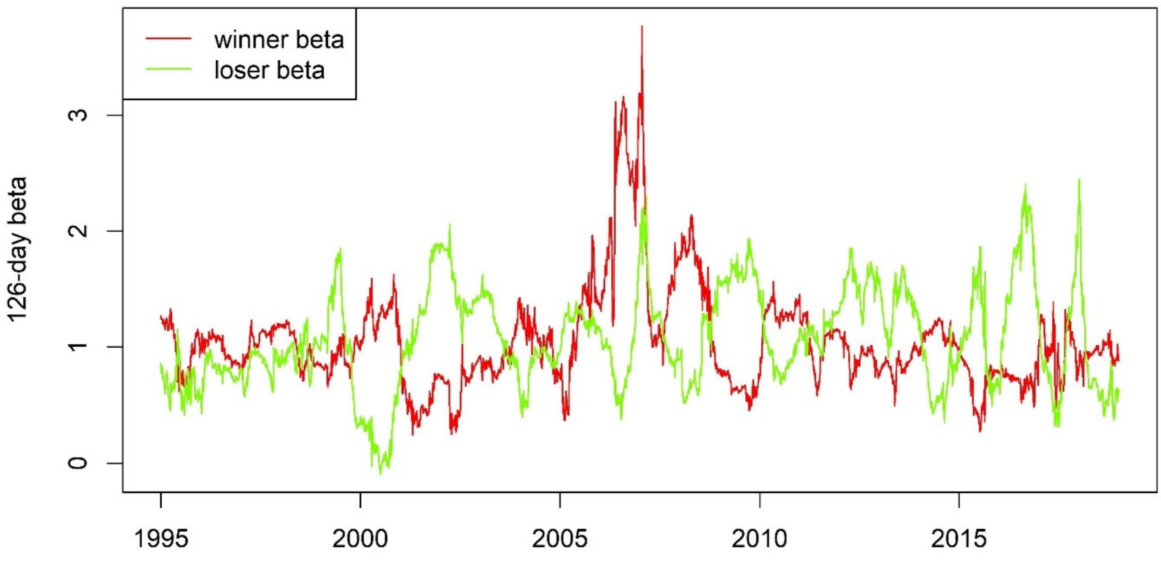




17-industry rolling betas:







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